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UNDERSTANDING THE EFFECT OF COMMUNITY RESOURCES ON DISABILITY EMPLOYMENT IN THE MOUNTAIN WEST

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By

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This study examines the relationship between community resources and disability employment rate in the Mountain West. It draws on the five categories of Social Determinants of Health (SDOH) as defined by the Office of Disease Prevention and Health Promotion (ODPHP) (2020) to select community resource variables. The determinants include: economic resources, health and health care, social and community context, infrastructure, and education. While there has been a good deal of work to understand how the SDOH can influence health outcomes, there has been little exploration of the influence that the SDOH has on employment outcomes for persons with disabilities (Frier et al. 2018). Studying community resources at the county level across the Mountain West provides insight into how spatial variation can impact employment of persons with disabilities. I used a hierarchical linear regression to examine the relationship between community resources and disability employment rate while controlling for socio-demographic factors and the rural-urban status of counties. This study found that four of five SDOH categories had a significant variable associated with disability employment rate. Significant community resource variables were: financial sector establishments, non-profit hospitals, rental vacancy rate, Housing and Urban Development (HUD) units, internet subscriptions, and education attainment. Results suggest that SDOH resources have an effect on rates of disability employment at the county level.

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1. INTRODUCTION

1.1 Background

Rural America experiences higher rates of disability, poverty, and unemployment than the rest of the nation (Gamm et al. 2010, Research and Training Center on Disability in Rural Communities 2019). Persons with disabilities in rural counties are more likely to experience unequal access to resources than those in urban communities (Iezzoni, Killeen, and O'Day 2006). In general, people in rural areas more frequently suffer poor health outcomes than urban populations, making for geographic health disparities (Lutfiyya et al. 2012, Office of Disease Prevention and Health Promotion 2020). An additional example of disparity among those with disabilities and among those living in rural communities is the rate at which people with disabilities are employed. Disability employment rate is a strong indicator of quality of life and equality (Geiger, Van Der Wel, and Tøge 2017). The concept of Social Determinants of Health (SDOH) was developed to understand how different types of resources within a community are related to health. Health disparities may be the result of differences in these resources between counties (Lathrop 2020) which may also affect disparities in employment.

Community resources can be thought of as the goods and services used to meet the needs of individuals in the community. The presence of, and access to, these resources help in understanding outcomes for persons with disability in rural communities (Greiman and Ravesloot 2016; Myers and Ravesloot 2016). With increased access come opportunities for increased utilization, especially of health and employment services (Mueller et al. 1999; Jang, Wang, and Lin 2014). The goods and services considered here are tangible resources within the community measured at the county level. The intangible resources, such as social capita and trust, were not considered in this study as they are challenging to capture quantitatively and often occur at a finer geography than the county level (Hindman and Yamamoto 2011).

Socio-demographic variables impact both health and employment outcomes (Smedley et al. 2003). Race and poverty have impacts on one's access to healthcare and employment opportunities.

Poverty status is a complex variable that is often linked to other demographic and economic attributes, with rural areas frequently experiencing higher rates of poverty than urban areas (Tickamyer and Duncan 1990). It is important to acknowledge these interactions and control for them to understand employment opportunities for persons with disabilities.

1.2 Objective and Approach

The objective of this study was to understand the relationship between community resources and employment rate for those with disabilities in the Mountain West Census division. The dependent variable was disability employment rate. Disability employment rate, or the rate that people with disabilities are employed, is a strong indicator of disability equity and quality of life (Geiger, Van Der Wel, and Tøge 2017).

Community resources make up the independent variables of this study. The SDOH framework was used to identify community resources associated with disability employment, when considering community resources that best serve those with disabilities with respect to employment opportunities. The variables selected for this study were selected based on their standing in the literature and their relevance to the SDOH. Each category of the SDOH as defined by the U.S. Office of Disease Prevention and Health Promotion (ODPHP) was captured by the selected variables. In addition, socio-demographic control variables, namely race and poverty, were selected to account for the well-known impact socio-demographic factors have on outcomes for those with disabilities. A binary variable was created to capture any discrepancies that might exist between rural and urban counties. This variable was based on 2020 U.S. Office of Management and Budget statistical delineations on metropolitan and nonmetropolitan counties.

The selected variables drew from a large dataset of county level indicators which align with various SDOH. I employed a hierarchical linear regression model to examine the relationship between the dependent variable (disability employment rate) and community resources after accounting for socio-demographic control factors and a rural/urban interaction. This model could offer insight into which community resources have the most influence or association with disability employment rate.

2. CONCEPTUAL FRAMEWORK

To piece together the different aspects of research that contribute to the foundation of this study I reviewed literature on disability employment rate, disability, the SDOH, how the SDOH relate to disability, and rurality. Connecting these bodies of literature allowed for a grounded approach in variable selection and modelling efforts.

2.1 Disability Employment Rate

Disability employment rate, or the rate at which persons with disabilities are employed, is a strong indicator of quality of life for persons with disabilities (Shabunova and Fakhradova 2017). In 2019 in the United States, 19.3% of persons with a disability were employed. For those without a disability the employment rate was 66.3% (Bureau of Labor Statistics 2019). While the Mountain West may have higher rates of employment than the national average, the 2019 disability employment rate for ages 18 to 64 was still 41.1% compared to the nondisabled population, aged 18 to 64, employment rate of 77.5% (U.S. Census 2019). This gap between the employment rate of persons with, versus persons without, disability is a strong indicator of disability inequity (Geiger, Van Der Wel, and Tøge 2017). This gap is slightly exacerbated by the rural-urban divide. In the rural Mountain West disability employment rate was at 39.7% in 2019 where in the urban Mountain West it stood at 42.2% (U.S. Census 2019). Rural areas tend to have lower rates of employment compared to urban. This is generally because rural areas have older populations that do not participate in the labor force, but even when that is accounted for with the prime-age population (ages 25 to 54) rural areas still experience lower employment rates than urban (ERS 2019).

Jang, Wang, and Lin (2014) identified factors that contribute to disability unemployment rates. They noted that educational attainment, sex, age, and marital status, greatly improved that rates of employment for those with disabilities, as well as the presence of job opportunities, stability of residency, and the presence of government services, such as a disability hiring quota (Jang, Wang, and Lin 2014). Similarly, in a study conducted by Shabunova and Fakrhadova (2017), it was demonstrated that the standard of living for those with disabilities was linked to disability employment opportunities, with employment opportunities often linked to one's mobility, access to job services, and educational attainment (Shabunova and Fakhradova 2017).

2.2 Disability

Disability is a complex concept that covers a variety of impairments and functional limitations. Persons with disabilities are considered to be the largest population minority in the United States (Bowen et al. 2020). The Centers for Disease Control (CDC) describes disability as an impairment in body function or structure, that causes activity limitations due to difficulties executing a task or action. These limitations can cause increased susceptibility to health problems and can impact access to health care (CDC 2020). Those with disabilities often experience social inequities, which combined with disability, often can lead to higher rates of morbidity and poor quality of life (Frier, Barnett, Devine, and Barker 2018). Inequities are also present in the labor force, with persons with disabilities, aged 18 to 64, having an overall employment rate of 37.1% in the U.S. when compared to the persons without disability population, aged 18 to 64, employment rate of 77.4% (U.S. Census 2019). A study led by Kavanagh et al. (2015) in Australia sampled 33,101 people for quality-of-life differences between those with disability and those without. The study found that overall, people with disability scored remarkably worse with regards to the socio-economic indicator scale used than those without disability. The study further revealed that among those with disability, women often fared even worse than men. Although the study noted that the type of disability was influential in the amount of disadvantage experienced, they were still able to conclude across the board that all disability types experienced a greater degree of socio-economic disadvantages. The measures used to indicate socio-economic standings included level of education, income, employment, and housing vulnerability. Housing vulnerability was defined as the number of individuals in the private renting market with an income in the lowest 30% of income distribution (Kavanagh et al. 2015). These measures align well with the SDOH as outlined by the U.S. ODPHP and will be expanded on in the following section.

2.3 The Social Determinants of Health

The SDOH, as defined by the U.S. ODPHP, are the conditions in which an individual is born, grows, lives, works, and ages. The U.S. ODPHP further break these determinants down into five main categories. These categories include economic stability, health and healthcare, social and community context, the neighborhood and the built environment (infrastructure), and education (Office of Disease Prevention and Health Promotion 2020). It is important to understand what contributes to each category and how they may influence health outcomes.

The concept of SDOH helps in understanding how socio-economic factors can impact health outcomes. It is well known that income, wealth, and education play a role in health outcomes. Breaking these factors down further to better understand the influence of economic and social factors on health outcomes can be challenging (Braveman and Gottlieb 2014). Braveman and Gottlieb have noted that social and economic factors can strongly influence health outcomes. These factors can include such things as employment and education. Where there are greater rates of employment, and higher levels of educational attainment and income, there tend to be fewer health disparities. With this, Braveman and Gottlieb observed that where there was less education, evidence of racial segregation, and low social support there was an increase in deaths associated with health issues that are often preventable or curable. Lathrop describes the SDOH as factors that impact chronic stress and the body's response to living in stressful conditions (Lathrop 2020). These conditions can be brought on by poverty, unsafe living conditions, abuse, food insecurity, oppression, and racism. Lathrop notes the importance these factors, as well as the broad understanding of SDOH as socio-economic influencers, have on human health and their impact on the health of certain demographic groups. Marmot et al. (2018) summarized the key findings of the Commission of Social Determinants of Health. They outlined that public access to resources within a community are essential for healthy living. One of their main recommendations in improving health equity across the board was increased access to community resources and a redistribution of these resources to be more equitable in how they are accessed. Marmot et al. went on to suggest that often urban areas are the focus of resources and funding to increase health equity, and that rural areas are often underinvested in. Given this oversight, more resources need to be allocated to rural areas to increase health outcomes for rural residents (Marmot et al. 2008).

2.4 Disability and the Social Determinants of Health

A study by Hanson et al. (2003) found that those with disability suffer greater socio-economic and health-related disparities when compared to their non-elder counterparts without disability (Hanson et al. 2003). The authors argue that the implication of these disparities causes greater limitations in daily activity and cause greater rates of unemployment. Their findings revealed that those with disabilities use the healthcare system more frequently than those without disability. This finding stresses the importance of the healthcare system resources for those with disabilities. Frier et al. (2018) studied the connection between disability and the SDOH. They studied how SDOH were influenced by the onset of a disability and the health outcomes of individuals. The study showed that above all else income was the most important of the SDOH as income levels often decreased with the onset of a disability while spending, specifically on medical procedures and health care, increased. Disability was found to have a cascading effect on all measures of SDOH as one measure often influenced another. Negative effects on housing, transportation, social interactions, and personal relationships were all reported (Frier et al. 2018).

Tulsky et al. (2015) conducted a study to determine which economic factors best assess quality of life for those with disabilities. They found that cost of healthcare, access to housing, and reduced employment were among the contributing factors of unemployment and associated income loss. This study was informed by the U.S. Bureau of Labor Statistics showing that unemployment was higher among those with disabilities than those without (Tulsky et al. 2015). Research by Hall, Kurth, and Hunt (2013) on employment as a health determinant for working-aged people with disabilities found that those who held any paid employment positions had an overall better quality of life and were more likely to have better health and health behaviors (Hall, Kurth, and Hunt 2013). This work suggests that there are important interactions between the SDOH resources, quality of life, and employment among those with disabilities.

2.5 Rurality

The U.S. Census' urban/rural divide has played a large role in data collection and analysis. The dichotomy of urban versus rural is not entirely clear. Ratcliffe et al. (2016) describes the ambiguity of urban and rural as a spectrum between urban and rural landscapes. Cities expand, suburbs form, and sprawl continues until it either turns to rural landscape or meets another population hub (Ratcliffe et al. 2016). A definition widely used in research is the metropolitan/non-metropolitan definition. A non-metropolitan county is generally defined as a county containing an urban core of less than 50,000 people. These definitions are statistical delineations created for the county level by the U.S. Office of Management and Budget (OMB) based on populations and population clusters (U.S. Census Bureau 2017) (Appendix Figure A1).

Employment rates in rural areas have consistently been lower than the employment rates in urban areas. This trend has been attributed to the aging population in rural areas (ERS 2019), but it should also be noted that rural areas often experience disability at a higher rate than urban areas (von Reichert, Greiman, and Myers 2014). Rural areas have a history of poverty linked to extractive industries and agriculture. They tend to be areas with a small labor markets that lack diversity and jobs that pay livable wages. In general, rural areas are further from educational institutions than urban areas, which has been linked to the lower rates of education attainment observed in rural counties when compared to urban (Gurley 2016).

Rurality has interesting implications on the geographies of populations and resources. It has been well established that rural areas often suffer from economic hardships, socio-economic disparities, and an overall lack of resources when compared to an urban setting (Mueller et al. 1999). Mueller et al. documented in a review of rural geography literature that these disparities and lack of resources are often felt by specific demographics within the community. Minority and elderly populations in rural areas often had less access to health care than their urban counterparts. They believed that this may be due to economic status but acknowledged that resources were being underutilized as well. Resource underutilization, they went on to state, was likely the result of socio-economic status and direct access. At the time, Mueller et al. did not link health conditions to health inequities experienced in rural communities. They left the question of increased health issues open to further study, which would ultimately give way to studies on health disparities in rural communities, but also on how those with disabilities are impacted by rurality (Mueller et al. 1999).

3. METHODS

This analysis set out to shed light on how community resources, at the county level and as outlined by the SDOH, can impact disability employment rates in the Mountain West. A hierarchical linear regression was used to examine the relationship between disability employment and community resources while also taking socio-demographic control variables and rural/urban classifications into account.

3.1 Research Setting

The focus of this study was on the Mountain West or Census Division 8 (U.S. Census 2018). This region is made up of eight states, including Arizona, Colorado, Idaho, Nevada, New Mexico, Montana, Utah, and Wyoming (Figure 1). Together these states have a total of 281 counties. Of the 281 counties, 65 are metropolitan and 216 are nonmetropolitan, of which 69 are micropolitan and 147 noncore counties. I selected this region for my study area because I conducted this research out of the University of Montana, which is in Division 8. There is also other research that used these delineations as study areas and I would like to contribute to this body of Census division area research (Otterstrom and Shumway 2003).

While the Mountain West takes up a sizeable portion of the U.S. land area, it only houses about 7.5% of the total U.S. population (U.S. Census 2018). A little over three quarters of the counties in the region are non-metropolitan. The landscape has few urban areas with large stretches of rural land in between. The population is made up of predominantly white individuals, with racial and ethnic minorities, including Hispanic, accounting for only 16.6% of the population. This racial makeup is relevant as race is an important predictor of disability (Smedley 2003).

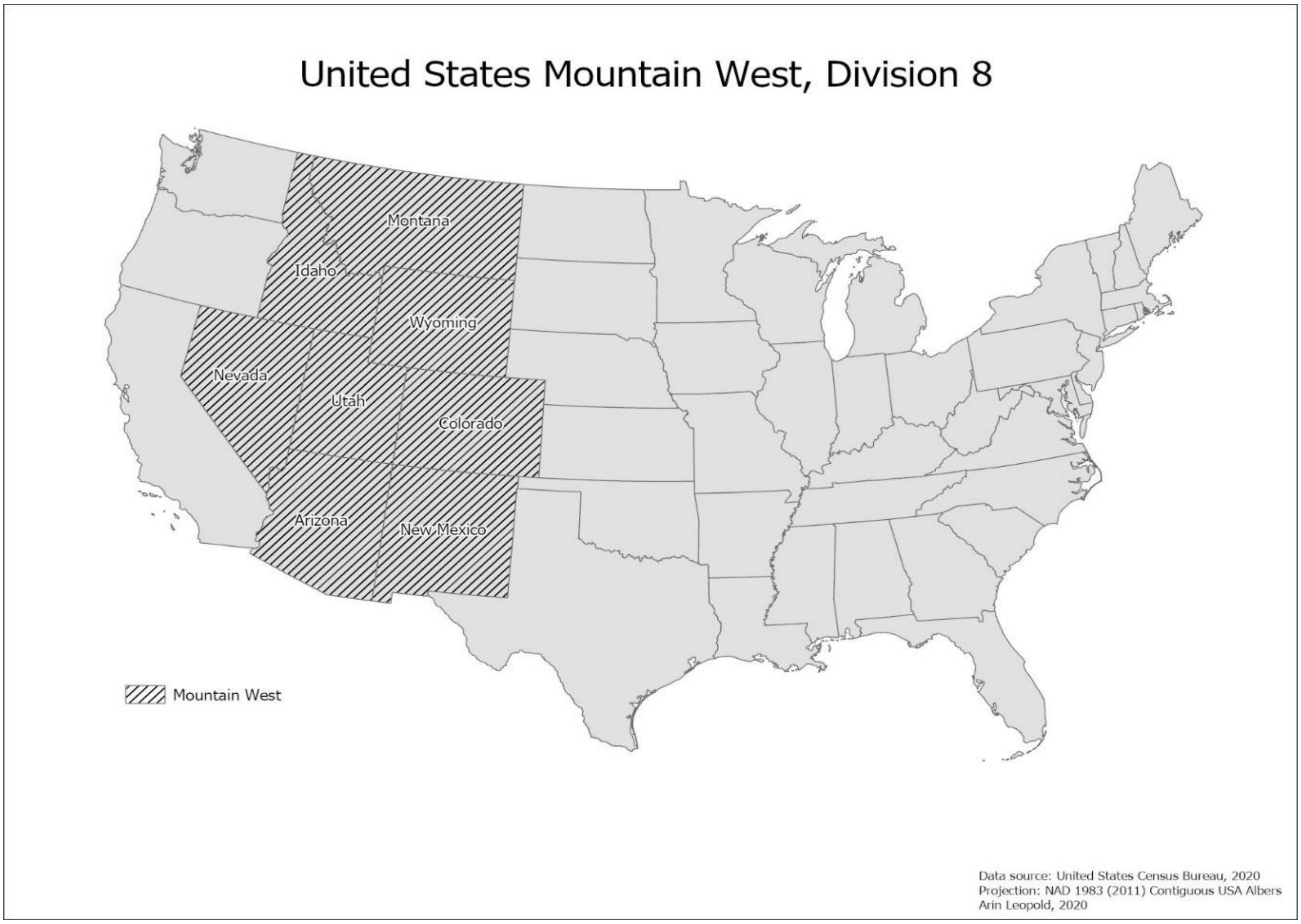

Figure 1: Census Division 8, the Mountain West. Source: U.S. Census Bureau 2020.

While disability is experienced by all races, it disproportionately affects minorities, especially as the population ages (Figure 2). In the Mountain West, Black and American Indian and Alaskan Natives experience disability at a higher rate than their white counterparts. In the age group 65 and up, the American Indian and Alaska Native population experiences disability at rate of 49.5%, nearly half of their population.

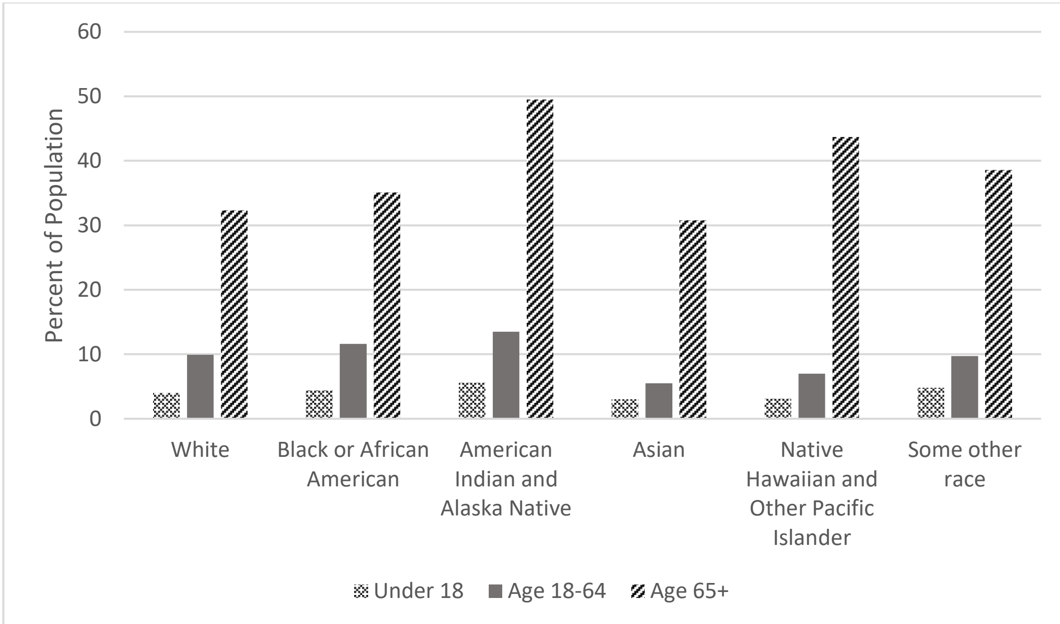

Figure 2: Disability by Age Group and Race in the Mountain West. Source: ACS 2019 5-year Table S0201.

Employment and economic growth in the nonmetropolitan Mountain West have largely outpaced the employment and economic growth of the United States for some time (Vias 1998). Employment in the Mountain West has shifted over the past decades from extractive industry to a more amenities-based economy. This shift came with a growth in population and has led to the development of a larger service industry (Vias 2005). In recent years, the Mountain West has continued to see a shift from a resource-based economy to a natural and cultural amenity-based economy (Ooi et al. 2015). Today, the Mountain West has an employment rate of 63.7%, 0.3% higher than the national rate of 63.4% (U.S. Census 2019). Examining employment rate further shows the disability employment rate for ages 18 to 64 in the Mountain West is 41.1%, compared to 77.5% for those with no disability (U.S. Census 2019).

Beyond the shift in economic structure over the years, it is also important to note that today 13.1% of the region is below the poverty threshold, slightly lower than the national average of 13.4% (U.S. Census 2019). For education attainment. 88.9% of the population in the Mountain West hold the equivalent to a high school diploma or higher, which is slightly higher than the national average of 88.5% (U.S. Census 2019). This higher rate of education attainment may increase the rate of disability employment throughout the region.

3.2 Data Sources & Measures

The dependent variable, disability employment rate, was pulled from the American Community Survey (ACS) 5-year 2014-2018 table C18120 ages 18 to 64 (Appendix Figure A2). Disability employment rate has been linked to better health and quality of life for those with disabilities (Hall, Kurth, and Hunt 2013). While federal policies and healthcare suggestions play a role in one's desire and ability to work while experiencing disability, it is also contingent on the community's ability to support employment opportunities (Jang, Yun, and Meng 2014).

This research draws on a county level database of community resources created as part of the Research and Training Center on Disability in Rural Communities (RTC:Rural) grant. The variables were diverse and suitable to capture the five categories of SDOH as defined by the ODPHP (Lathrop 2020), including: economic resources, health and health care, social and community context, infrastructure, and education (Office of Disease Prevention and Health Promotion 2020). I used regional Census codes to limit the national dataset down to the Mountain West division of the United States and identify counties as metropolitan or non-metropolitan to take into account rural-urban differences specifically.

The dataset is made up of variables from the following data sources:

- U.S. Census
- CBP – County Business Patterns
- ACS – American Community Survey
- NCES – National Center for Education Statistics
- NCCS – National Center for Charitable Statistics
- CMS – Center for Medicare/Medicaid Services

- SAMSHA – Substance abuse and mental health services
- CHR – County Health Rankings
- USDA – U.S. Department of Agriculture
- BJS-LEC – Bureau of Justice Statistics Law Enforcement Core
- HUD – Housing and Urban Development
- FTA – Federal Transit Association
- IMLS – Institute of Museum and Library Services
- ILRU – Independent Living Research Utilization
- ACL – Administration for Community Living
- ARDA – Association of Religious Data Archives

3.2.1 Variable Selection

The dataset of community resources created by RTC:Rural outlined above was used to select the independent variables for this study. This was done through a systematic approach of categorizing variables into the SDOH categories. Added to the selection of SDOH variables were socio-demographic control variables and the metropolitan/nonmetropolitan county variable. Many of the variables in the dataset are limited across the region and were not available in every county. These variables were dismissed due to the amount of missing data. I used a correlation matrix to remove variables that were not strongly correlated with disability employment rate. The research literature was consulted to further justify the variable's use in this study. If there was no strong supporting literature the variable was not included. The variables outlined below follow the order in which they were entered into their repective blocks and the model (with results presented in Table 4).

Economic Sectors

Disability unemployment coexists with shortages in distinct economic sectors (Vornholt et al. 2018). To take economic sectors into account, U.S. Census County Business Patterns (CBP) data showing establishments by economic sectors were included, which are based on the North American Industry Classification System (NAICS). I found establishment sectors 23 (construction), 52 (finance), and 54 (professional, technical, & science) to be most correlated with disability employment rate (Appendix Figures A3-A5). These sectors may have an association with disability employment rate that is the result of labor market growth or the services these sectors provide for persons with disabilities. While these sectors do not necessarily have the highest rates of disability employment among the economic sectors (Paul, Rafal, and Houtenville 2020), they still may influence the outcomes for persons with disability for the role they play in the community. It is hypothesized that a greater presence of these sectors favorably affects employment opportunities for persons with disabilities and consequently increases the disability employment rate.

Primary Care Physicians

This variable is used to capture access to, and availability of, healthcare in a given county (Appendix Figure A6). While not a perfect representation of one's access to healthcare, it suggests ties to one's ability to find and access medical treatment. Those with disabilities can have difficulty finding physicians who understand their disability and are also available without insurance or with Medicaid (Hanson et al. 2003). In a study conducted by Iezzoni, Killeen and O'Day (2006), interviewees had the general perception that rural areas have less healthcare offerings and often have less access to healthcare than urban areas. Areas poorly served by healthcare providers may have lower rates of employment among those with disabilities because healthcare needs may not be met (Iezzoni, Killeen and O'Day 2006). Counts of primary care physicians used in this study were collected from the County Health Rankings (CHR).

Hospital Nonprofits

Hospital nonprofits can be important in providing access to healthcare in a community. These nonprofits include hospitals that operate 24 hours a day, but also can offer other services such as health support and mental health treatment (NCCS 2019). Hospital nonprofits are also associated with providing jobs and services in a community that help with healthcare access and facilities. These nonprofits may help provide employment to those with disabilities and may contribute to an increase of quality of life (Bielefeld 2000). Hospital nonprofit data used in this study was accessed through the National Center for Charitable Statistics (NCCS) (Appendix Figure A7).

Religious Congregations

Religious congregations play an interesting role in the community. When aspects of theology and faith are set aside, they can be viewed as nonprofit associations and voluntary organizations. In general, religious congregations are thought to contribute to society in areas where the public sector and the nonprofit sector may not have reached. This can mean playing an important role in the community, such as providing homeless shelters and meals, or organizing fundraises and support networks (Cnaan and Curtis 2013). The relationship religious congregations have to disability employment is unclear. They may offer a community support network, which may compensate for limited public support and in turn could have a positive effect on the rate of employment for those with disabilities. Religious congregation data was gathered from the Association of Religious Data Archives (ARDA) (Appendix Figure A8).

Rental Vacancy Rate

Rental vacancy rate is an indicator of the relative shortage or surplus of existing rental housing. It has been used to classify socio-economic status in neighborhoods and as a general indicator of economic activity (U.S. Census 2021). Rental vacancy rate has been linked to employment dynamics in an area. Broadly speaking, a low vacancy rate can be indicative of a community that is seeing high employment rates. Specifically, rental availability may decrease with the influx of people brought about by employment opportunities (Wong et al. 2018). One would expect a negative association between employment rates and vacancy rates which may carry over to disability employment rate. Rental vacancy rate was gathered from the ACS 5-year survey 2015-2019 (Appendix Figure A9).

HUD Units

The U.S. Department of Housing and Urban Development (HUD) is largely focused on alleviating housing costs for low-income households and providing access to affordable housing in areas with increased social and economic opportunities. This allows for the use of income on essentials other than housing for those who qualify for HUD programs (Dawkins and Jeon 2018). In 2016, 91% of households living in public housing met HUD's definition of very low income. Additionally, over half of the heads of household in public housing were either over the age of 62 or had a disability (Doctor and Galvez 2019). HUD units have been linked to health improvements among adults and higher rates of met medical needs. HUD unit recipients have improved access to healthcare and increased physical activity among low income non-senior adults (Wong et al. 2018). An increase in access to affordable housing may contribute to an increase in employment opportunities for persons with disabilities, however because HUD public housing units are often placed in areas with low income, there may be a negative association with disability employment rate. HUD data was made available by the U.S. Department of Housing and Urban Development (Appendix Figure A10).

Internet Subscription

The idea of a "digital divide" has gained traction recently in the context of access to healthcare. Those who have access to internet, and the understanding of how to use it, were found to have increased access to healthcare opportunities than those who do not (Heath 2021). Persons with disabilities have been shown to have less access to the internet than those without disabilities. Having accessible technologies to address the internet access gap between those with disabilities and those without may increase economic inclusion for persons with disabilities (Scholz, Yalcin, and Priestley 2017). Rural areas of the country have less internet infrastructure than urban areas and as a result may have less access to healthcare opportunities. Internet is not just important for healthcare, however, and in recent times has become a pivotal part of employment with the pandemic-induced increase in working from home. Internet, therefore, may lend itself to more employment opportunities and better access to healthcare (Heath 2021). This study used the percent of the population that has an internet subscription as the measure of internet access, with high rates of internet access expected to have a positive relationship with disability employment rate. Internet subscription rates were collected from the ACS 5-year survey 2015-2019 (Appendix Figure A11).

Education Attainment

According to the U.S. Bureau of Labor Statistics, those who have obtained higher education levels are more likely to be employed than those who have not. This applies to both those with disabilities and those without (Tulsky et al. 2015). Disability has also been used as a predictor of education attainment. Those with disabilities often attain lower level of education than persons without disability, which has long-term implications on employment opportunities and earnings (Cox and Marshall 2020). For this study, education attainment was measured as the rate of those 25 years of age and older who do not have a high school diploma or equivalent and was collected from the ACS 5-year survey from 2014-2018 (Appendix Figure A12). Higher levels of education attainment are expected to have a positive relationship with disability employment rate (Vilorio 2016). Conversely, a high share of the population with low levels of education is expected to depress the employment disability rates.

Race

Race has long been defined as a determinant of health that can lead to health inequities. Race is thought to be associated with socio-economic factors that affect where people live, their income, their level of health insurance, and even variations in life expectancy (Williams 2012). Race is also thought to be a key factor that leads to disparities in healthcare access. This can be the result of racial segregation influencing education and employment opportunities. Race is often associated with high levels of poverty which can lead to limited healthcare opportunities (Caldwell et al. 2017). To analyze race in this study, percent of population variables were used from the ACS (Appendix Figure A13). This variable was entered into the model as a control variable and was calculated as the percent of the population in a county that is nonwhite and includes Hispanic.

Poverty

Poverty is more prevalent in rural areas than in urban areas. This observation has been associated with a limited opportunities as a result of social and economic factors, including employment. (Tickamyer and Duncan 1990). Those with disabilities are more likely to be in poverty than their counterparts without disability. The implications of poverty impact access to transportation, healthcare, employment, and education (Frier et al. 2018). For this study, poverty was used as a percentage of the population in poverty. This variable was entered as a control variable and was collected from the ACS 5-year survey from 2014-2018 (Appendix Figure A14). I would expect a high poverty rate to be associated with low disability employment rates.

Rural - Urban OMB Codes

These OMB definitions of metropolitan and non-metropolitan are statistical delineations created for the county level by the U.S. Office of Budget and Management (OBM) based on populations and population clusters (U.S. Census 2017) (Appendix Figure A1). By these delineations, a metropolitan county is defined as having an urban core with greater than 50,000 people, and a nonmetropolitan county is defined as a county with an urban center less than 50,000 people. For the purpose of this study, I binary coded OMB classifications as metropolitan being equal to 0, and nonmetropolitan being equal to 1. This effectively defines urban as metropolitan counties and nonmetropolitan (rural) counties as all others by

OMB definitions. The metro/nonmetro variable is included here to explore whether there are independent urban-rural effects, after accounting for SDOH and socio-demographic controls.

3.3 Analysis

Examining the relationship between disability employment and community resources reflecting SDOH is at the core of this research. In this analysis, the dependent variable was disability employment rate, defined as the rate of people with disabilities employed within the labor force. Employment has been shown to be a valuable indicator of quality of life for persons with disabilities (Hall, Kurth, and Hunt 2013). Explanatory variables were selected to capture community resources that are associated with the social determinants of health. Control variables account for well-known socio-demographic factors that influence employment outcomes poverty and race. The output coefficient for the OMB variable will give insight to the role rurality plays in disability employment rates.

The dataset included a range of variables with different scales of measurement, including continuous, categorical, and ordinal. Categorical and ordinal data, such as the presence of primary care physicians, were converted into rates, thereby creating continuous variables. Rates were created by dividing the count of a continuous or ordinal variable in each county by the population of the county and multiplying the result by 10,000 people, showing how many instances of that variable are present per 10,000 people in each county. The data was reduced to core components by considering the reviewed literature behind each variable and the number of cases each variable contained. Variables with missing data points were disregarded. The dataset was created to ensure that each category of the SDOH was represented in the model. Table 1 below shows the SDOH categories, the variables used that fall within each category, as well as additional control and geographic variables used in this analysis. Shown are also the abbreviations used throughout the modeling process, the variable data source, and the original variable form, such as counts or rates.

Categories	Measured Variable	Abbreviation	Source	Raw Variable Form
Economic	Establishment sector 23 (construction)	estab_23	CBP	counts
	Establishment sector 52 (finance)	estab_52	CBP	counts
	Establishment sector 54 (professional, technical, & scientific)	estab_54	CBP	counts
Health and Healthcare	Number of Primary Care Physicians	prim_care	CHR	counts
	Number of Nonprofit Hospitals	Np_hosp	NCCS	counts
Social and Community	Religious Congregation Count	relcon	ARDA	counts
Infrastructure	Percent of Vacant Rental units per County	vac_rate	ACS	rate
	Number of HUD public housing units	hud_pubunit	HUD	counts
	Has Internet Subscription	hasintsub_rt	ACS	rate
Education	Less than Highschool Diploma or GED	hs_gedless_rt	ACS	rate
Control	Percent Non-White including Hispanic	Nonwht	ACS	rate
	Percent in Poverty	Pov_per	ACS	rate
Geography	Metropolitan/Nonmetropolitan	OMB_dummy	OMB	nominal

Table 1**:** Variables selected for this study.

The next subsections will outline the process by which the variables were standardized, and the regression method used to analyze the data.

3.3.1 Transformations

Each variable was converted to a rate, if not already, to standardize raw counts and make the variables more comparable.

$$variable_{rate} = \left(\frac{variable_{count}}{population}\right) * 10{,}000$$

While each variable was converted to a rate, not all variables behaved the same way. Using normalized variables is important for being able to compare different measures in common regression procedures. Variables that were sparse throughout the study site would exhibit skewness to the right. To overcome skewness and to make the variables more normally distributed, some variables were transformed using a log transformation. In each case of a log transformation, the variable was converted using the following equation:

$$variable_{log} = \log_{10}(variable_{rate} + 1)$$

where $variable_{log}$ is the converted variable after the log transformation and $variable_{rate}$ is the variable after being converted to a rate. Each variable was converted as $\log_{10}(n_{rate} + 1)$ because in cases where $variable_{rate}=0$ the variable would be undefined if it had not undergone a linear shift.

The OMB binary variable was left as binary in the model. This means that in the regression a coefficient multiplied by the OMB variable when equal to 1 represented micropolitan and noncore counties. If the value is 0 it represented metropolitan counties.

Table 2 below shows the transformation each variable underwent for standardization and the form the variables were originally in. Maps of each transformed variable can be found in the appendix.

Category	Measured Variable	Original Variable Form	Variable Transformation
Economic	Establishment sector 23 (construction)	counts	rate & log(n+1)
	Establishment sector 52 (finance)	counts	rate & log(n+1)
	Establishment sector 54 (professional, technical, & scientific)	counts	rate & log(n+1)
Health & Healthcare	Number of Primary Care Physicians	counts	rate
	Number of Nonprofit Hospitals	counts	rate & log(n+1)
Social & Community	Religious Congregation Count	counts	rate & log(n+1)
Infrastructure	Percent of Vacant Rental units per County	rate	none
	Number of HUD public housing units	counts	rate & log(n+1)
	Has Internet Subscription	rate	none
Education	Less than Highschool Diploma or GED	rate	none
Control	Percent Non-White Including Hispanic	rate	none
	Percent in Poverty	rate	none
Geography	OMB Metropolitan/Nonmetropolitan	nominal	binary

Table 2**:** The variable transfromations applied to each variable to create a standardized form to be used in the final model.

3.3.2 Statistical Procedures

A hierarchical linear regression model, which is used here, enters variables in blocks and models their relationship to the dependent variable using Ordinary Least Squares (OLS) to show how one block can predict the dependent variable versus another block (IBM 2009). This makes the model unique in that it can be used to consider grouped variables in sequence. Entering a block of control variables second will help to understand how the independent variables (block 1) captured the variability among disability employment rate without accounting for known predictors of employment. This model used three blocks. The first block was the SDOH independent variables. The second block controlled for the socio-demographic variables outlined above. The third block entered in the OMB variable to detect whether rural-urban classification impacts the relationship between the SDOH variables and disability employment after controlling for socio-demographic factors. In other words, using a hierarchical linear regression for this analysis helped to explain what the relationship is between the SDOH independent variables and disability employment rate after controlling for county-level measures of race, poverty, and rurality. Prior to running the model, collinearity was tested at a VIF cutoff of less than 5 to ensure low correlation among the independent variables were present (O'brien 2007).

While this method of analysis can inform how disability employment rate is predicted by the variables that make up each block, there are limitations in how accurate this can be over a geography. The binary coded OMB codes will serve as a geographic input into the model. While this can inform if rurality is a predictor of disability employment rate, it may not capture some of the nuances of how the independent variables predict the dependent variable over space. With this limitation in mind, I also examined the Global Moran's Index of Spatial Autocorrelation (Moran's I) for each variable to aid in further discussion of how this model performs. Moran's I is a measure of correlation among a case and nearby locations, it essentially is a statistic between a variable and its spatial weight (Moran 1948). In this study the Moran's Index looks at the county value for the variable the index is being created for and the neighboring county values.

4. RESULTS & DISCUSSION

The SDOH independent variables, control variables, and the metropolitan/nonmetropolitan variable were able to predict 44.3% of the variability among the data (table 3). While not all variables stood out as significant, those that did lend insight into which community resources may be useful in impacting disability employment rate. This chapter include the results of the model, a discussion of results, and an analysis of the model residuals and spatial statistics

4.1 Model Results

Hierarchical linear regression was used to examine how county level community resources can explain disability employment rate within the scope of the social determinants of health. The variables were entered into the regression in three blocks. The first block consisted of independent variables of community resources drawn from SDOH framework, the second block includes socio-demographic control variables, and the third block adds the OMB metro-nonmetro code intended to capture urban-rural differences in the model. Overall, the model showed an R^2 of 0.440 after the first block, an R^2 of 0.441 after the second block, and an R^2 of 0.443 after the third block. The change in R^2 from the first block to the second block was 0.001, and from the second block to the third block was 0.002 (Table 3). SDOH variables account for 44.0% of the variability among the data. After controlling for the socio-demographic variables and rurality, 44.3% of the variability is captured. This shows that SDOH independent variables on their own show a fairly strong relationship to disability employment rate. While the final model with all three blocks is slightly better, the difference is minimal. The adjusted R^2 decreases between the first and second block, suggesting that the contribution of the control variables was insignificant between blocks. Looking at the coefficients and significance for the final model shows what best predicts disability employment rate and how.

Block	R^2	ΔR^2	Adjusted R Square	Std. Error of the Estimate
1 – SDOH Variables	.440	--	.419	9.247312850
2 – SDOH + Control Variables	.441	.001	.416	9.273739992
3 – SDOH + Controls + OMB variable	.443	.002	.416	9.274515708

Table 3: Model fit for each variable block.

4.2 Discussion

Table 4 shows regressions results from the third block. Six SDOH variables stood out as significant. These variables included: establishment sector 52 (finance), nonprofit hospitals, vacancy rate, HUD units, percent with internet subscription, and education attainment. The socio-demographic control and the OMB variable used to represent rurality were not significant.

Blocks	Categories	Variable	Variable Name	b	Std. Error	beta	T	Sig.
			Constant	-0.680	6.874		-0.099	0.921
SDOH - Community Resources	Economic	Sector 23: Construction	LG1_estab23	4.849	3.192	0.103	1.519	0.130
		Sector 52: Finance	LG1_estab52	18.938	3.664	0.291	5.169	**0.000**
		Sector 54: Profess-Techn-Scient	LG1_estab54	2.387	3.575	0.054	0.668	0.505
	Health & Healthcare	Primary Care Physicians	prim_care_rt	-1.253	0.782	-0.090	-1.603	0.110
		Nonprofit Hospitals	LG1_np_hosp12	34.055	8.306	0.205	4.100	**0.000**
	Social & Community	Religious Congregations	LG1_relcon	0.204	3.528	0.004	0.058	0.954
	Infrastructure	Vacant Rentals	Vac_Rate	-0.256	0.086	-0.150	-2.977	**0.003**
		HUD Public Housing Units	LG1_HUD_units	-4.714	1.297	-0.195	-3.636	**0.000**
		Internet Access	hasintsub_rt	0.348	0.108	0.266	3.220	**0.001**
	Education	Less than HSD or GED	hs_gedless_rt	-0.200	0.089	-0.163	-2.253	**0.025**
Control	Socio-demographic	Non-White incl. Hispanic	nonwhthisp_per	0.033	0.044	0.054	0.748	0.455
		Poverty	pov_per	-0.035	0.145	-0.017	-0.242	0.809
Geo-graphy	Rural-Urban	Metro-Nonmetro OMB	OMB_dummy	1.631	1.668	0.057	0.977	0.329

Table 4: Model Coefficients and Significance

The significant variables in this model capture each category of the social determinants of health, aside from social and community, at a brightline cutoff of 95% significance.

Many of the significant variables in the model followed expectations relating to disability employment rate. For the SDOH linked to the economic determinant, establishments in sector 52, the finance sector, had a positive relationship with disability employment, with finance having a beta coefficient of 0.291 and significance of 0.000. This implies that counties with high employment in the finance sector tend to have better labor market opportunities leading to higher rates of employment for those with disabilities. It could be that employment in the finance sector is more amenable for persons with disabilities. A sizeable finance sector may also indicate strengths in other sectors more broadly and economic growth in general, boosting the employment rate for persons with disabilities. Conversely, in counties with fewer establishments in finance, rates of employment of persons with disabilities are diminished.

For the health determinant, the rate of nonprofit hospitals also had a positive relationship with disability employment with a beta coefficient of 0.205 and a significance of 0.000. This is in line with the thinking that increased access to healthcare service leads to better health outcomes which in turn leads to better quality of life. Better health presumably allows for successful engagement in the labor market leading to higher employment rates of persons with disabilities.

All three infrastructure variables considered here are statistically significant. Vacancy rate exhibited the hypothesized relationship with a beta coefficient of –0.150 with a significance of 0.003. Counties with low rental vacancy rates show higher disability employment rates. On the other hand, counties with ample vacancies show lower disability employment rates. This is in line with the idea that higher rental vacancies are indicative of a weaker economy, while a tight housing market – with low vacancies – is more commonly observed in areas with a strong labor market, offering better employment opportunities (Anghelache 2018).

The rate of public HUD units exhibited a relationship with disability employment rate contrary to the hypothesis with a beta coefficient of -0.195 with a significance of 0.000. This model suggests that as the presence of HUD units decrease, disability employment rate increases. This relationship seems complex. It may exhibit a similar relationship to disability employment rate as rental vacancies do, where housing incentives and available housing might be more frequently offered in areas experiencing economic struggles. While a VIF cutoff of 5 was used to ensure there was no collinearity among the data before running the model, it is still worth noting that typically a coefficient might present the opposite sign of what was hypothesized due to collinearity. HUD units are often placed in areas with higher rates of poverty, so it may have been possible that collinearity between the standardized HUD units variable and the poverty variable existed. The VIF for the standardized HUD units variable was 1.376 and for poverty rate it was 2.396.

Having an internet subscription also positively interacted with disability employment rate with a beta coefficient of 0.266 with a significance of 0.001. Counties with high shares of internet subscriptions also have a higher disability employment rate. Access to internet at home through internet subscription appears to improve opportunities in labor markets. This is in line with recent findings in how access to internet can increase certain outcomes for those with disabilities, including employment (Heath 2021).

The measure of education, the percent of population, aged 25 and older, with less than a high school diploma or equivalent, had a beta coefficient of -0.163 with a significance of 0.025, indicating that areas with a high population share with less than a high school education or equivalent have low disability employment rates. This relationship suggests that more people in a county attaining education favorably affects employment opportunities leading to higher disability employment rates. It could also imply that counties with a high proportion of people with a high school diploma or more make a labor force appealing, which may attract potential employers, which in turn leads to more employment opportunities.

Against expectations, there are no significant effects of religious congregations, used here to capture the Social and Community determinant, on disability employment rate. It could be that religious congregations operate at the neighborhood and community level, not the county level. It also could be that the support offered by religious congregations may not be related to improving employment opportunities.

The two control variables were not significant in the model. Poverty rate and the race variable both did not contribute to the overall model as predicted. While it is understood that non-white races experience disability at a higher rate than their white counter parts, it may be more nuanced than race alone. Race may not be a significant component of this model due to other factors, such as age. Referring back to Figure 2 in section 3, it is worth noting that disability increased as age increased for all races, it is possible that a significant portion of those with disabilities who are also nonwhite may be out of the work force and would not be a part of the overall disability employment rate.

The metropolitan/nonmetropolitan OMB variable was insignificant in the final model. The adjusted R^2 value from the second block to the third block, used to adjust for a natural increase in R^2 values when more variables are added to a regression, did not change when the metro/nonmetro binary variable was added. Nonmetropolitan counties, used to capture rural counties across the Mountain West, did not have an impact on the model. Though there are higher rates of unemployment, disability, and poverty in rural communities this model suggests that there may be other factors at play when using rurality to explain disability employment rate. This may be because OMB codes were not the best measure of capturing rurality, but it also could be because of how nuanced measuring a rural area can be. Transportation networks, distance to resources, and access to resources all play a role in how a community can best serve individuals, whereas measurements of rural only tend to look broadly at population counts within a geography (Gamm and Hutchison 2003).

4.3 Residual Analysis and Spatial Statistics

An analysis of residuals and Moran's Index was used to interpret how well the model fit the data. The residual plot of the model (Figure 3) shows a random pattern with a Loess line of best fit that stays close to zero with no obvious trend, implying that the model appropriately fit the data and analysis. While some outliers fall outside of two standard deviations from the mean, a majority of the residuals stay within two standard deviations. We can assume that the relationship between the response and the predicters is zero due to the Loess line and the clustering around zero. This indicates that the model used was likely the appropriate type of model to use in this study, and that the model predictions are not the result of chance due to the wrong model fit.

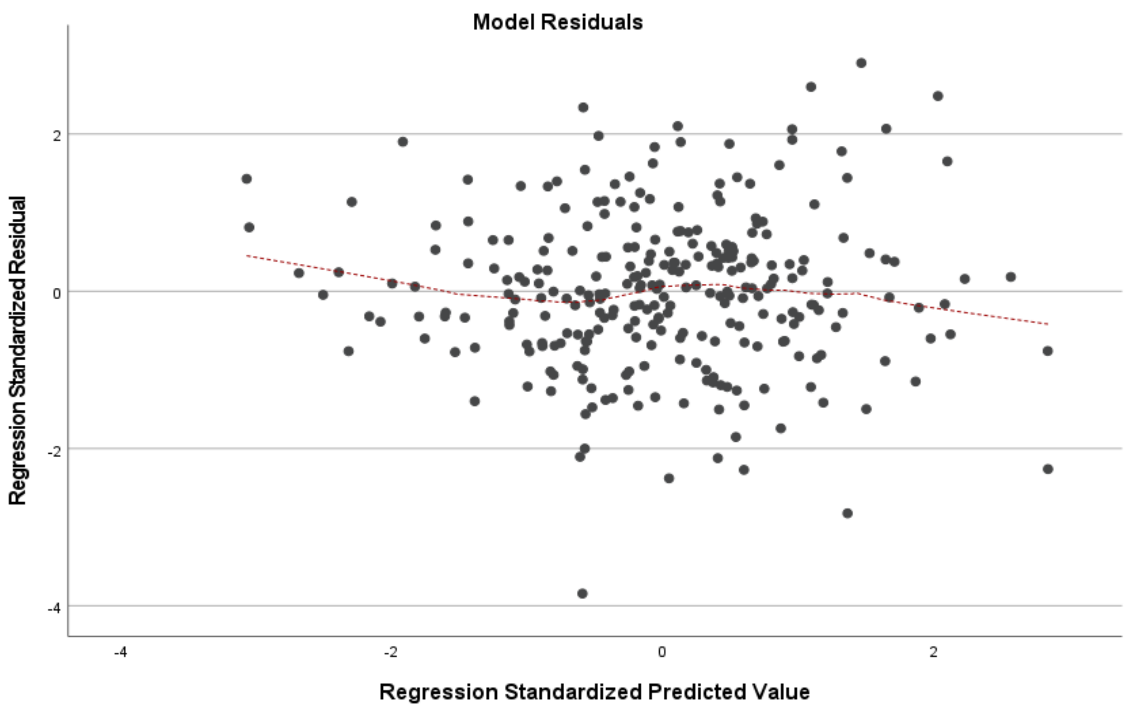

Figure 3: Standardized Residuals

Figure 4 shows where the model is over and underpredicting disability employment rate and the context of those predictions with respect to surrounding counties. Counties where the model predicts a higher disability employment rate than what the disability employment rate actually is will have negative residuals and will appear as a shade of blue on the map. Counties where disability employment rate is lower than what the rate actually is will have a positive residual and will appear as a shade of orange. A random pattern is ideal for a residual map showing model predictions as it shows that there are no outlying geographic factors influencing the model.

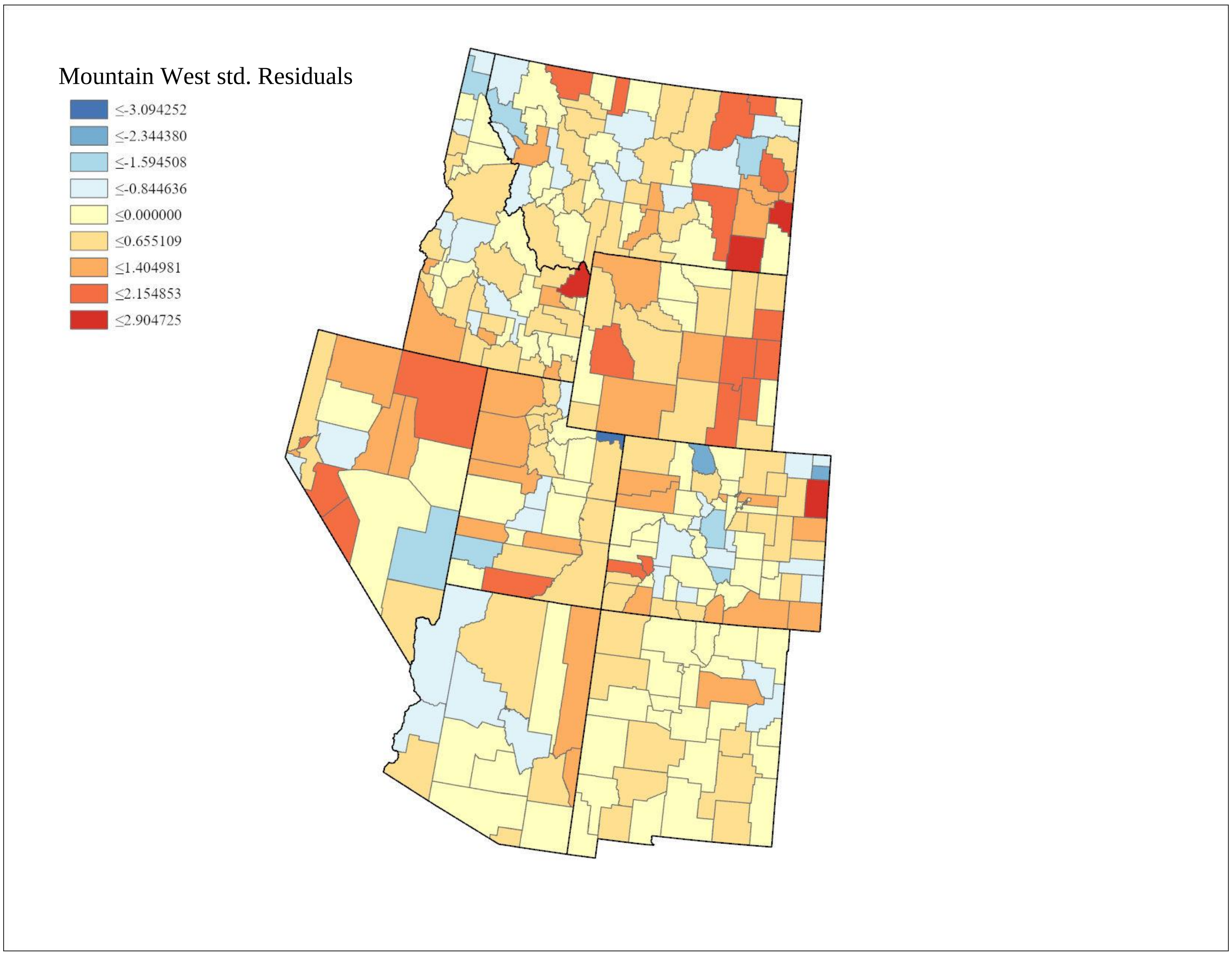

Figure 4: Map of Standardized Residuals

To show how the model residuals varied spatially throughout the Mountain West, the Moran's Index for the residuals was calculated. The Global Moran's I for the residuals was 0.159128 and had a significance of 0.000008. This value indicates that there is slight clustering among the residuals and that there may be a spatial component that was not captured by the model. To further investigate how variables are clustering, the Global Moran's Index was calculated for each significant variable (Table 5). The Moran's I for these residuals indicate that this model may be failing to capture a spatial component of the data.

Variable	**Moran's Index**	**Significance**
DIS_EMP	0.30747	<2.2e-16
HASINTSUB_RT	0.50051	<2.2e-16
LG1_ESTAB_52	0.16014	7.611e-6
LG1_NP_HOSP12	0.28374	4.001e-15
VAC_RATE	0.19241	8.414e-8
LG1_HUD_UNITS	0.26103	4.689e-13
HS_GEDLESS_RT	0.30014	<2.2e-16

Table 5: Moran's Index for Significant Variables

Local Indicators of Spatial Autocorrelation (LISA) are used to measure spatial autocorrelation among cases within a geography. Figure 5 shows a LISA for the residuals of the model used below. Clusters are identified as low or high values surrounded by counties with like values. Outliers are identified as cases surrounded by counties with values unlike them. For example, a county with a high residual surrounded by counties with low residuals will stand out as a high-low outlier. These clusters and outliers are helpful in honing in on where exactly the model is mispredicting disability employment rate and the nature of that predicition, similar to the the residuals plot, a random geographic pattern would be ideal, as it shows that the model is not being influenced by an outside geographic component that was not captured by this model.

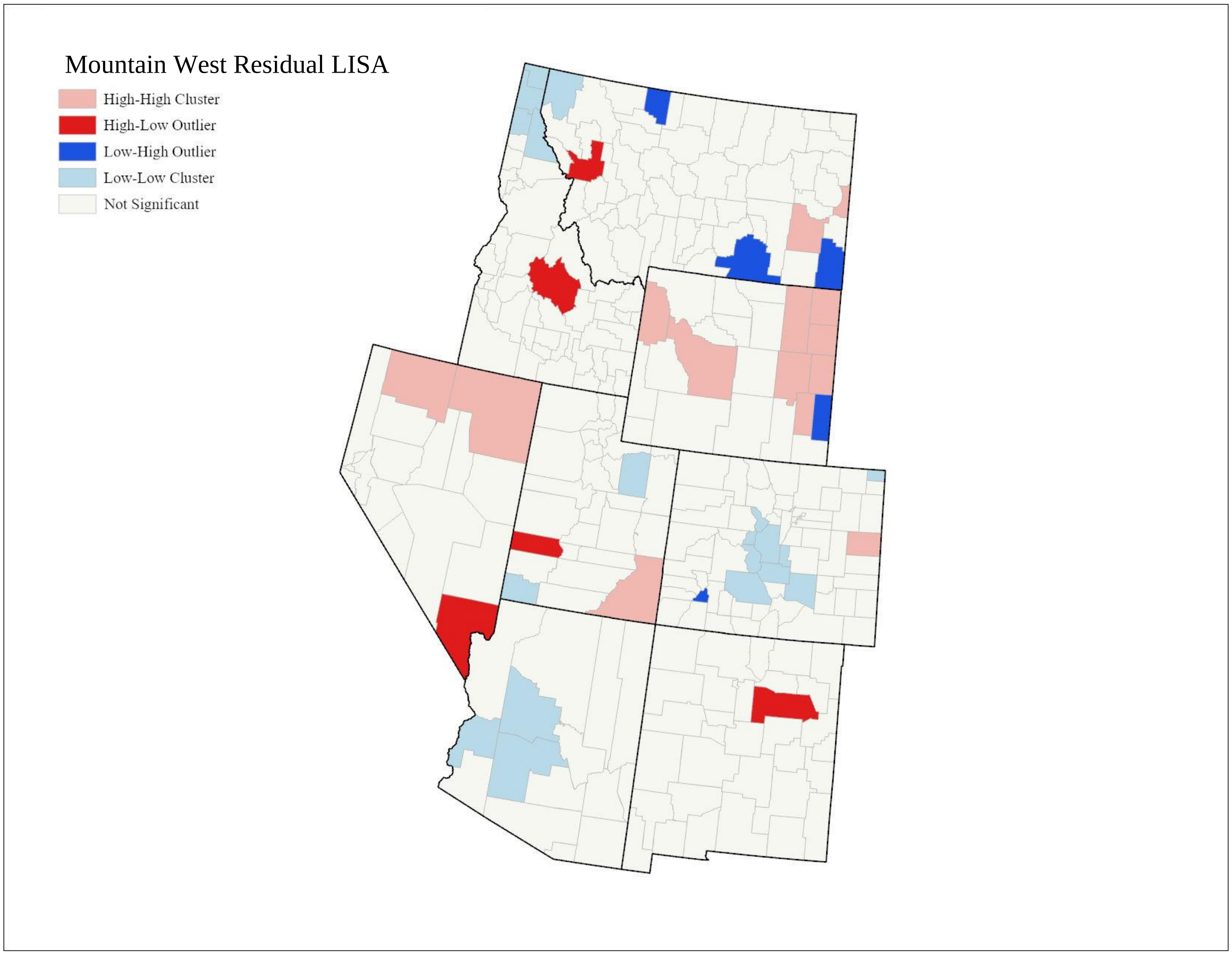

Figure 5: LISA for Residuals

To better apprehend how space can influence disability employment rate, a model that uses a spatial weighting matrix might better capture the relationship between the independent variables and disability employment rate. While counties allow for a broad regional analysis of community resources, they do not analyze disability employment at the individual level. Using counties as the unit of analysis for a spatial understanding also has its drawbacks. The counties are confined within the larger geography of the United States, with many counties lying on the edge of the geographic boundary, creating an edge effect that limits spatial interpretation.

5. SUMMARY & CONCLUSION

Persons with disabilities make up the largest minority group in the United States (Bowen et al. 2020). While disability affects every demographic, it does not affect each demographic group equally. Besides disability differences by race and age, as shown in Figure 2, inequity for persons with disabilities also plays out is the labor market. The rate of employment for persons with disabilities is lower than that rate for persons without disability indicating unequal labor market opportunities (U.S. Census 2019). As the disability employment rate is seen as a proxy for the quality of life (Geiger, Van Der Wel, and Tøge 2017), its importance reaches beyond the scope of employment.

To examine disability employment rate throughout a region is therefore to also examine geographic inequity. Geographic differences are well documented in disability research, with rural America experiencing disability at a higher rate than the rest of America (von Reichert, Greiman, and Myers 2014). However, less is known about geographic differences in disability employment, and about the factors contributing to it. This research examined disability employment based on the premise that community resources available in an area impact employment opportunity for persons with disabilities. Socio-demographic controls and a rural-urban variable were included as well.

To examine the complex relationship between community resources and disability employment rate over a broad geography, the SDOH framework was chosen for selecting the use of explanatory variables. This approach allows, in a systematic way, for exploring a wide range of variables from a variety of sources that could be compiled and used in a geographic study with counties as units of analysis. The hierarchical linear regression model used, employing SDOH, socio-demographic control and a rural-urban variable, accounted for 44.3% of the variability among the data. This attests to the influence SDOH community resources have on disability employment rate. Model outcomes also imply that much about disability employment is left unexplained. Disability employment rate seems to be more nuanced than what can be captured by county-level community resource variables used here, which draw upon the SDOH framework. That said, an important takeaway from this study is that there are certain aspects of a community that appear to improve the rate of employment for those with disabilities in the Mountain West. The factors that seemed to favorably influence disability employment rate were the presence of financial sector establishments, nonprofit hospitals, internet subscription rates, and higher levels of education attainment. Factors with unfavorable effects on disability employment rates were higher rental vacancy rates and higher rates of HUD public housing units. One broad finding of this study is that several SDOH categories were represented by a significant variable in the model. Each one of these variables can be explored further to unpack their relationship to disability employment rate. For instance, the presence of financial sector establishments may be associated with a thriving economy and positive economic growth in an area, which would benefit disability employment and the community as a whole. Conversely, HUD public housing units are often invested in low-income areas (Doctor and Galvez 2019) and therefore might be more prevalent in poorer counties and associated with lower rates of employment. This study explores each variable’s relationship to disability employment rate, but it is limited in offering a full explanation of the deeper reasons beyond quantitative measures on a sizeable geographic area. There may be other explanations for the observed relationships that could benefit from a qualitative approach on a finer geographic scale.

Findings from this study suggest that community resources play an important role in predicting disability employment rate. The presence of these resources can influence the disability employment rate in a county. Quite clearly, other strategies could have been used that do not filter community resources through the SDOH framework. Also, while the variable used to capture the rural component of this study did not stand out as significant, it is important to note that a rural-urban divide still exists with many of the variables used in this study, and that while this study may not have supported the impact that divide has on disability employment rate, it is still worth questioning and examining. There are many definitions of rurality. In designing research a series of decisions must be made to move forward with analysis, but it would be interesting to examine different definitions of rurality to see if some definitions capture rurality better than others. Similarly, other definitions of disability employment rate could have been used as well.

The definition of disability employment rate used in this study uses the noninstitutionalized civilian population with a disability ages 18 to 64, but a different definition that strictly deals with labor force participation or the prime age population could have been used. All in all, I chose the definitions that I did because of their grounding in literature, their availability, and scalability with the county level unit of analysis.

It is difficult to apply results at the county level to the individual, or in this case an individual town or community, but one takeaway from this study that might be applicable to a local community is that the presence or absence of the significant variables in this study may have a larger impact than we might think on the employment rate of people with disability and local equity in general. Seeking out the resources in this study that had a significant relationship with disability employment might have positive impacts on a local community, whether that be more internet infrastructure with affordable plans, better access to primary care physicians or hospitals, or investing more resources into attaining education. Adding resources to a community seems like an intuitive act to make a community a better place to live but taking stock of what resources are available and where any gap in resources might lie has important implications. Increasing the significant community resources found in this study could have cascading effects in a community. Increased employment, equity, and access to resources would likely improve the quality of life for those within the community. These resources should be considered and advocated for when investing in a community. If this study were to inform policy, it would be by first suggesting that the labor market inequities between persons with disabilities and those without be further investigated to begin to get at the heart of the issue. Understanding why this discrepancy exists will lead to further insight in the role community resources play at the community level. While each community in the Mountain West will likely have similarities between them, they ought to be considered on a case-by-case basis when looking to improve the lives of persons with disabilities. Simple steps to increase availability and access to the resources shown to be significant in this study could improve the lives of persons with disability by providing necessary resources to increase employment opportunities and quality of life.

It is also worth noting that the variables that were not significant leave some questions unanswered. To begin to unpack why these variables did not contribute to the model, further analysis must be conducted. Were they insignificant because they do not contribute to disability employment specifically in the Mountain West or is it because there are deeper underlying factors involved that make them insignificant beyond the scope of this analysis? Each variable was selected for its association with disability employment rate, for its support by the research literature, and its relationship to the SDOH framework. Having potentially relevant variables left out could raise questions about an omitted variable bias, while including additional variables without grounding in the literature could yield spurious results. By supporting each variable choice with literature and its relevance to the SDOH, the model results were more likely to be accurate representations of each variables association to disability employment rate.

To explore the possibility of a spatial component that may not have been captured by this model, the Moran's Index was calculated for each significant independent variable, the dependent variable (table 4), and the model residuals. Each variable showed some form of clustering with significance which implies that there may a spatial component left to be explored. This clustering could exist due to the nature of how each variable is dispersed throughout the region, with the southern portion containing more of one variable than the northern portion or vice versa, or it could be clustering in urban areas when compared to rural. That said, exploring in depth the spatial component of the variables was not within the scope of this study. While clustering did exist with significance in the residuals, the clustering was low, and the LISA (Figure 6) showed no obvious pattern of where the residuals were clustering. This slight clustering again implies that a spatial component may not have been captured by the model, but not to the extent where the linear hierarchical regression model presented here could be dismissed altogether.

Disability employment rate in the Mountain West is just one facet in the broad field of disability research and policy. Advocating for increased visibility for the rights and equity of persons with disability, whether through voicing concerns of the resources available within a community or supporting the increase of infrastructure that benefits persons of disability, is an important step in creating a more inclusive environment. While further research into the employment opportunities, and how they are created, for persons with disabilities need to be explored, so do all other aspects of disability that lead to understanding and equity across the board.

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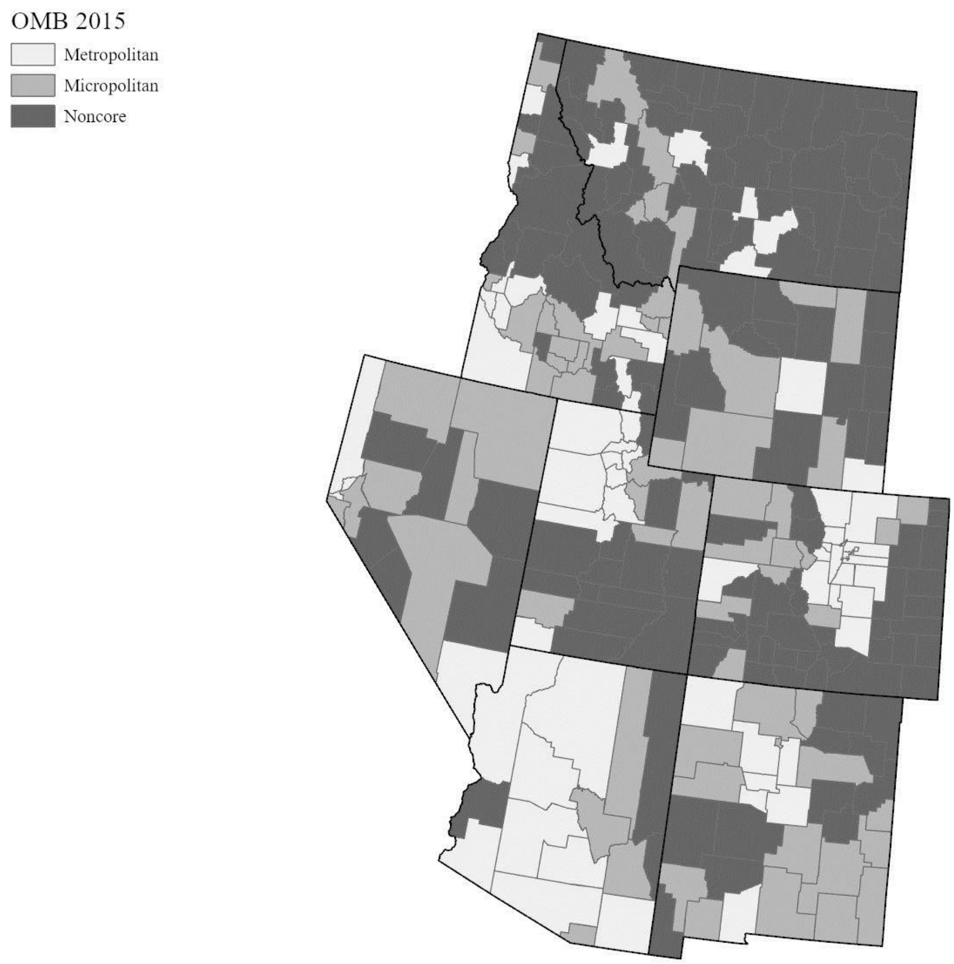
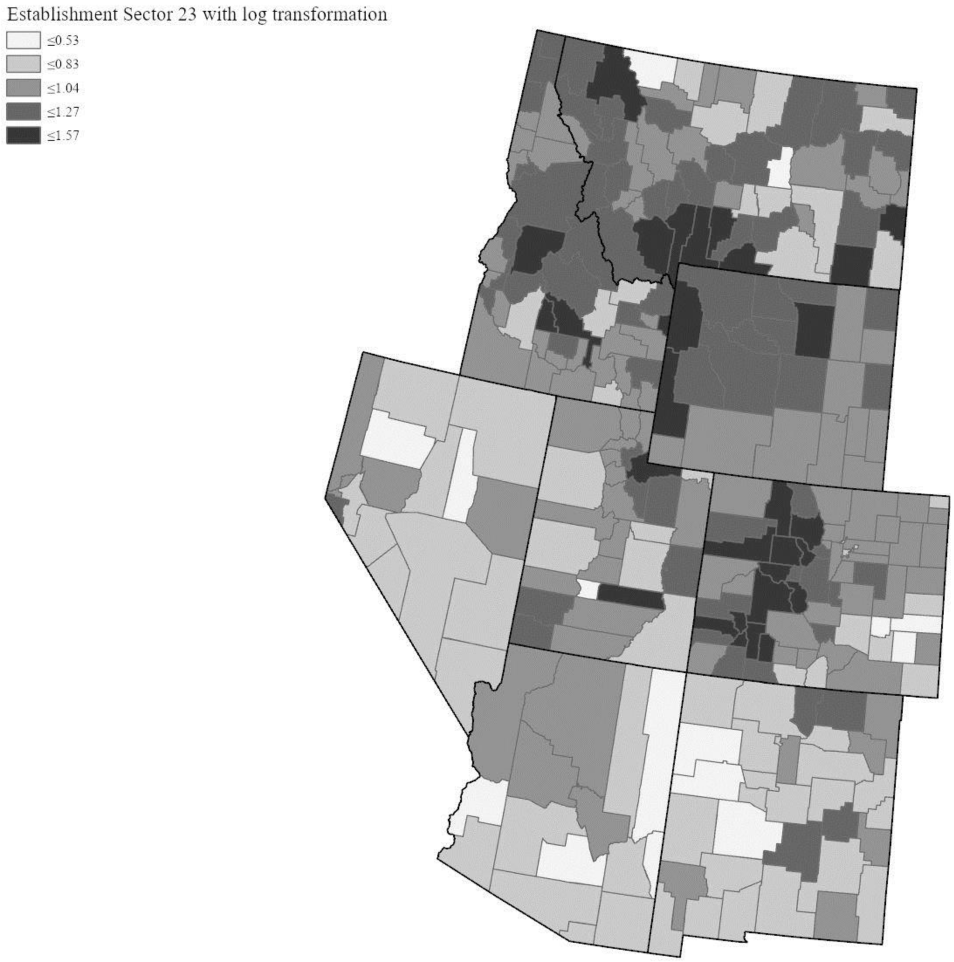
APPENDIX A: Variable Maps



A1: 2015 OMB classifications

A2: Disability Employment Rate

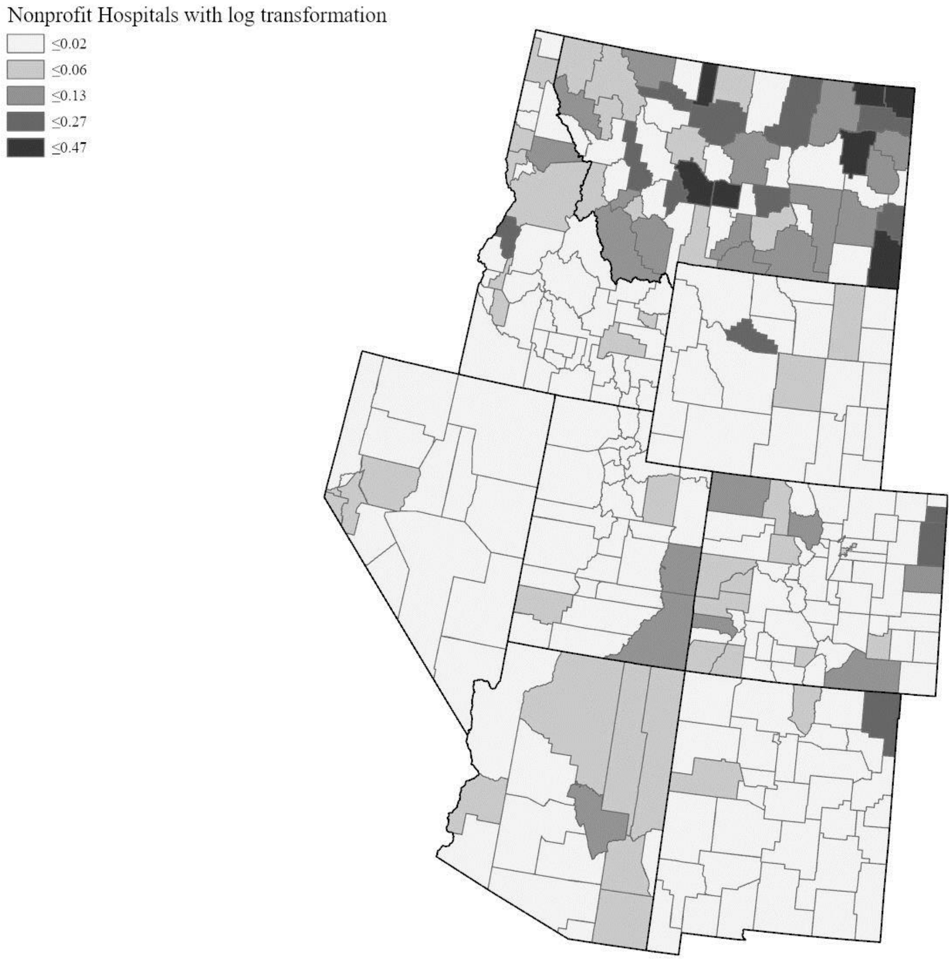


A3: Establishment Sector 23, Construction, with log transformation

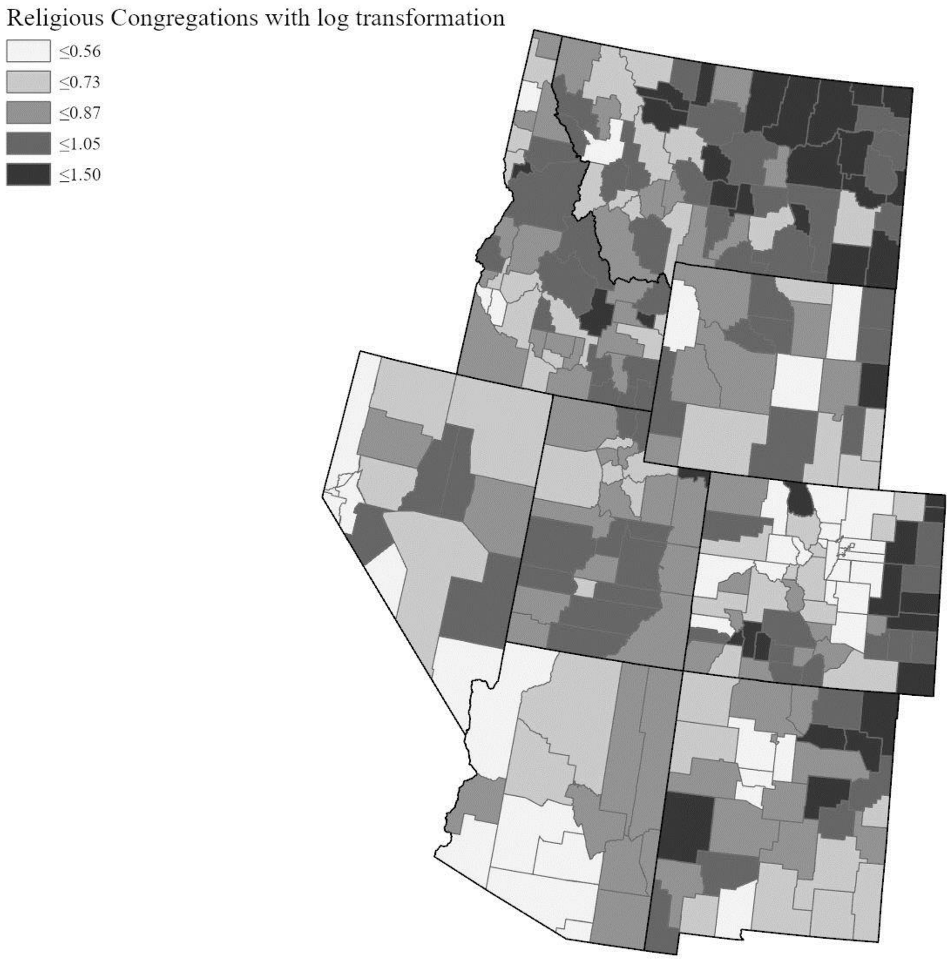
A4: Establishment Sector 52, Finance, with log transformation

A5: Establishment Sector 54, Professional, Technical and Scientific, with log transformation

A6: Rate of Primary Care Physicians



A7: Nonprofit Hospitals with log transformation

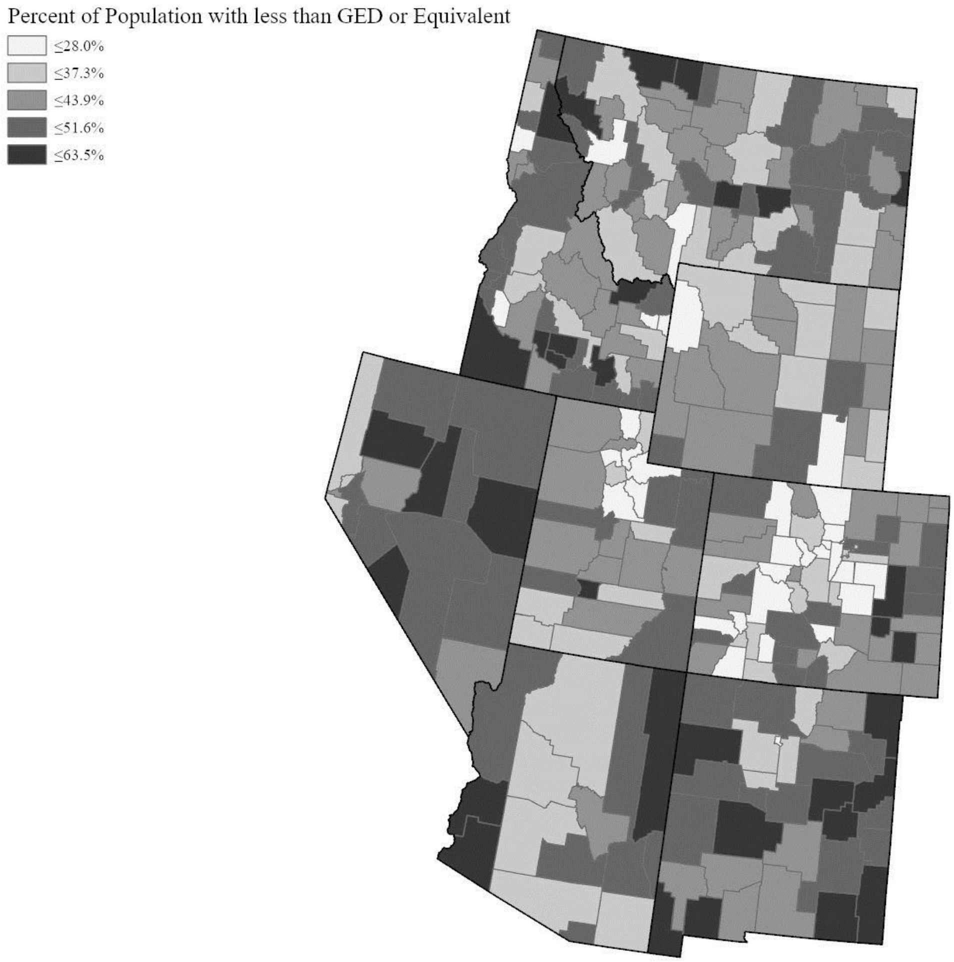


A8: Religious Congregations with log transformation

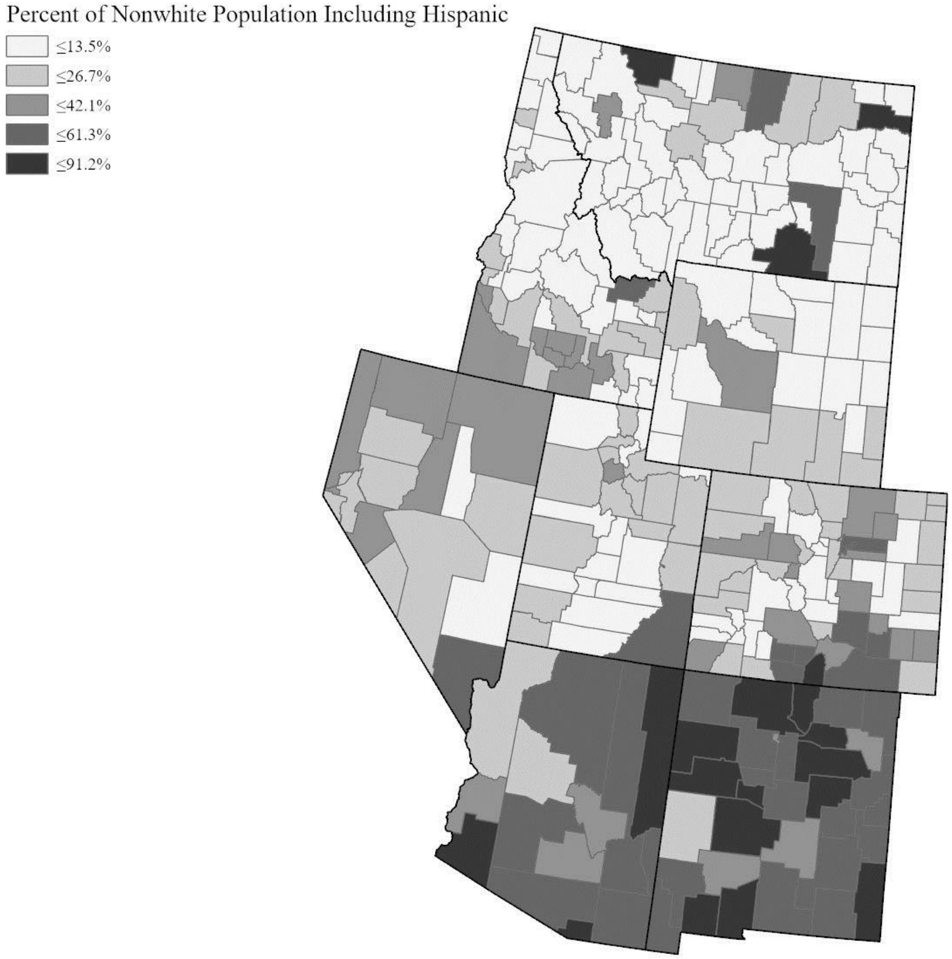
A9: Rental Vacancy Rate

A10: HUD Units with Log Transformation

A11: Percent of households with an internet subscription



A12: Percent of population with less than GED or equivalent



A13: Percent of nonwhite population including Hispanic

A14: Percent of population in poverty